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Serie Research Memoranda

The Role of Information in the Performance of Transport Networks

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ABSTRACT

Analysing flows in a transportation network is a complex task, especially when the system is congested. The underlying reason is that the traffic flows result from the interactions of all participants in the network. In this paper a simple simulation model for a congested transportation network is shortly described. In the model the individual interactions between the participants play a major role. The simplicity of the model makes it possible to focus attention on the effects of different kinds of information mechanisms on the resulting traffic flows.

In the presented model each individual travels several periods in the network. The route and departure time choice are made by using individual stochastic utility functions. A learning mechanism is used in these functions to model the individuals' experience of the situation in the network in the past. This implies that every next period the route and departure time choice are based on a better knowledge of the congested network.

The learning mechanism in the utility function can be changed to model more advanced kinds of information acquisition. Four different kinds of information mechanisms will be presented. One of these is a real-time information system (RTI) which has been in the centre of interest recently (e.g. the DRIVE-project).

Finally some simulations with the model are carried out. This is done with a program written in the language C. The congested network, used for the simulations, represents the major roads around Amsterdam in 1989. The simulations will lead to some interesting results. It will be shown among others that, depending on the way information is obtained in a congested network, following the shortest route in time will not always lead to the shortest travel time in the whole network.



1 Information as a Tool for Changing Travel Behaviour

Transport networks are increasingly faced with the problem of negative externalities (congestion, pollution) which tend to reduce the overall performance of networks. Apart from market solutions (e.g. charges), regulatory measures (e.g. car pooling stimuli), transport related instruments (e.g. parking policies) and technological options (e.g. low emission cars), information provision is increasingly regarded as a vehicle for improving the efficiency of networks. The implementation and application of information systems in transport networks is likely to offer new promising possibilities for tackling the congestion problem (and hence indirectly the environmental problem). Developers of route guidance systems strongly believe that information systems can reduce travel time and mileage in road transport. The main idea is that without information on road situations most drivers base their choices on inferior (biased or incomplete) knowledge on the situation in the network, which leads to poor route and departure time choices (Ben-Akiva et al., 1991). By proper information provision to (potential) drivers 'better' choices will be made due to an improvement of drivers' perceptions and knowledge, and hence road congestion will decrease as well as the travel times of individual drivers. Other researchers hold some reservations and argue that drivers, once provided with (estimated or real-time) information, will possibly face a situation of oversaturation, overreaction or overconcentration¹, with the consequence that congestion will remain unchanged or even increase. See for arguments amongst others Arnott et al. (1991), Ben-Akiva et al. (1991) and Mahmassani and Jayakrishnan (1991). Thus it is not a priori evident that information will lead to a reduction in congestion.

There is a need for a more rigorous analysis of the impacts of information on drivers' choice, based on a formal behavioural model describing the attributes and consequences of choices in case of presence and use of road information systems for drivers. By

¹Oversaturation means that a driver is not able to process the information on overall road situations in order to select the optimal individual route.

Overreaction occurs when drivers' reactions to information (e.g. route choice) lead to a shift in congestion from one road to another.

Information will lead to concentration if a great number of drivers choose the same best alternative. These three phenomena may offset the overall benefits of information provision and acceptance.

means of such a model, which will be presented in this paper, various information effects on drivers' behaviour can be traced. Moreover, the model gives way for implementing realistic road networks, so that the analysis is not limited to small networks as in most studies. See for example Mahmassani and Jajakrishnan (1991), Mahmassani (1990) and Arnott et al. (1990).

The paper is organized as follows. In Section 2 various typologies of information are concisely presented, while in Section 3 the main characteristics of a transport network are discussed. Section 4 presents then the simulation model used in our analysis, while in Section 5 four different information mechanisms are distinguished and analysed. Section 6 offers various simulation results, and finally Section 7 contains some conclusions.

2 A Typology of Information

Information can be subdivided according to three characteristics.

The first characteristic is the distinction between static and dynamic information. Static information remains unchanged during a long period of time and is not influenced by actual road conditions, so that it is ineffective in solving daily congestion problems. Such information however, may be useful for drivers unfamiliar with the network.² Dynamic information is information that is adjusted according the actual situation in the network. This kind of information may be effective in order to avoid congested roads in certain periods of the day. Especially in case of non-recurring congestion³, road users, if provided with dynamic information, can try to avoid congested road segments in order to save travel time.

The second distinction is between pre-trip and on-route information. Pre-trip information is given before the start of a trip, while on-route information is given during a trip. The most advanced information systems are on-route information systems, as they allow for flexible adjustments of drivers' behaviour.

² Static information may offer, for instance, navigational assistance to drivers who do not know the road network.

³ Non-recurring congestion is congestion due to e.g. accidents or bad weather.

The last characteristic makes a distinction in terms of the degree of reliability of the information. Information systems serve to predict (future) traffic flows in order to provide drivers with customized information on travel times on various relevant roads of the network. The reliability of such predictions is critical for its social value. In the centre of interest are nowadays the real-time information systems (RTI). These systems provide drivers with dynamic on-route information about the actual situation in relevant parts of the network. Implementation difficulties and prediction requirements for such systems are discussed in Boyce (1988). A more complete overview of different kinds of information can be found in Kokkota (1992).

Any advanced information systems model for road users should be able to include also RTI. In the simulation model presented in Section 4 of this paper both dynamic pre-trip and dynamic on-route information can be incorporated. Before presenting the substance of this model we will discuss briefly in the next section relevant features of road networks.

3 Characteristics of Transport Networks

A transport network consists of infrastructure (supply side) and individual drivers (user side). The word 'individual' stresses one of the main characteristics of a transport network: many individual users are involved in the road system, they cannot be excluded and all of them behave differently. Thus a thorough analysis of transport networks means a detailed study of many variations in behaviour between individuals. Furthermore, each individual tries - in his role of a 'sovereign' consumer - to maximise his individual utility by means of proper choices on his traffic behaviour. Thus the resulting traffic flows in the network represent essentially an individual user optimum.⁴ Another important characteristic of transport networks is the fact that - beyond a threshold level - drivers' choices are affected by the choices of other drivers in the same system. For example, a road may become congested if new drivers entering

⁴From the literature the term user equilibrium is known instead of the term individual user optimum. Nevertheless, the words individual user optimum will be used in this paper because we do not apply an equilibrium analysis so that the individual optimising process will not necessarily lead to an equilibrium solution.

the transport system choose the same road which was also chosen by many drivers in the recent past. This situation indicates a clear case of interaction between participants in a transport network. Ultimately the traffic flows all over the system are the result of these different behaviours and interactions. See also Figure 1.

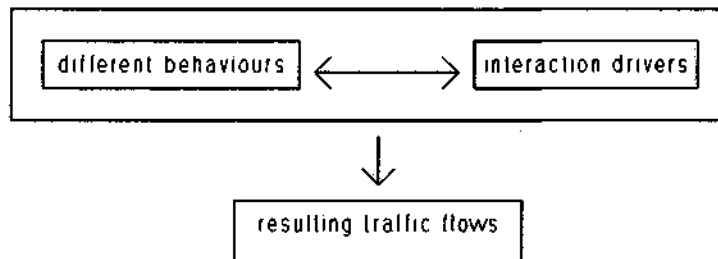


Figure 1: Traffic flows without information

The individual user orientation and the synergetic implications are the main reasons why analysing traffic flows in a transport network is a complex task and difficult to perform in a purely mathematical analytical context.⁵

Studying next information effects in a transport network is even more complex. If drivers are provided with information, there is not only interaction between the drivers in the network, but also between the information and the drivers. In fact, the information affects the choices of the participants, while at the same time these choices affect the information and the reliability of the information. This is schematically shown in Figure 2.

Using simulation models is an appropriate tool for analysing systems that are difficult to model in a purely formal mathematical way.

Although the model presented in the next section is very simple, it contains the main characteristics of a transport network exposed to an information system for road users. This model allows for the possibility to simulate different kinds of behaviours, the interaction between the drivers themselves and the interaction between the drivers and the information.

⁵The complexity of transport networks is evident from the work of Horowitz (1984), who has proven that even in a two-link network the stability of a stochastic equilibrium is not guaranteed. He had to resort to simulation experiments to analyse his most difficult model specification. Furthermore, he showed that oscillatory movements can already occur in a two-link network.

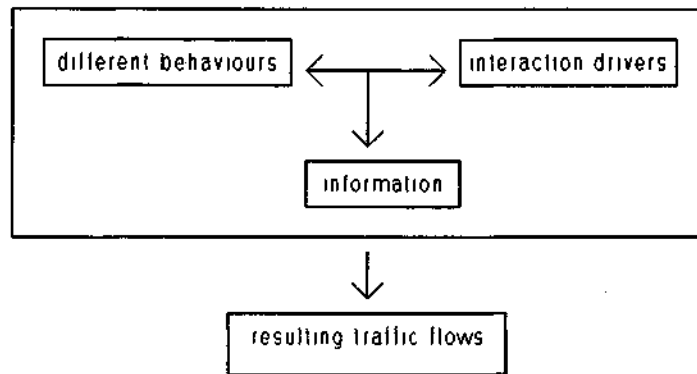


Figure 2: Traffic flows with information

4 The Pre-trip Version of the Model

The model developed here aims to simulate traffic flows in a congested network in a microscopic way during an arbitrary period of several days. To justify the simplifications used in the model it is necessary to assume that the network is congested during the simulation periods.⁶

Furthermore, we assume that on each day of the relevant period the same drivers make the same trip, so that in the relevant period the origin and destination never change for a driver. Thus, driver A_i has every day origin O_i and destination D_i .

Now we assume that driver A_i chooses each day between a given number of routes and a given number of departure times for travelling from O_i to D_i . So we abstract here in the short run from the so-called Choice Set problem (see for details Bovy and Stern, 1990).

In our model, it is hypothesized that drivers decide between routes and departure times according to an individual utility maximisation process and hence are assumed to behave rationally. The well-known random utility theory is used here to model drivers' behaviour. Each driver tries to make an optimal arrangement of available alternatives (an alternative consists of a route and a departure time) and chooses

⁶In congested networks it is reasonable to assume that the speed of a driver is only dependent on the density and flows in the network. We will make this assumption throughout the paper.

the one with the highest utility. In fact, we may take for granted that each driver makes a choice according to his own discrete choice model (Ben-Akiva and Lerman, 1985). This discrete choice method is often used to model drivers' behaviour (see for example Bovy and Stern, 1990). As each road user aims to optimise utility, the consequence would be that the resulting traffic flows (the meso configuration of the system) represent an individual user optimum (see also Section 3). This means that the flows are the result of an individual optimisation process of all users in the transport system.⁷ It seems plausible to conjecture that by the end of the day, when all drivers have finished their trips, they use their trip experience for deciding on the route and departure time decision the next day. In this way a learning mechanism is introduced in the discrete choice model. Figure 3 schematically shows the pre-trip model version. The same model hierarchy can be found in Ben-Akiva et al. (1991). Later on we will show that steps 2 and 3 must be modified if on-route information is introduced.

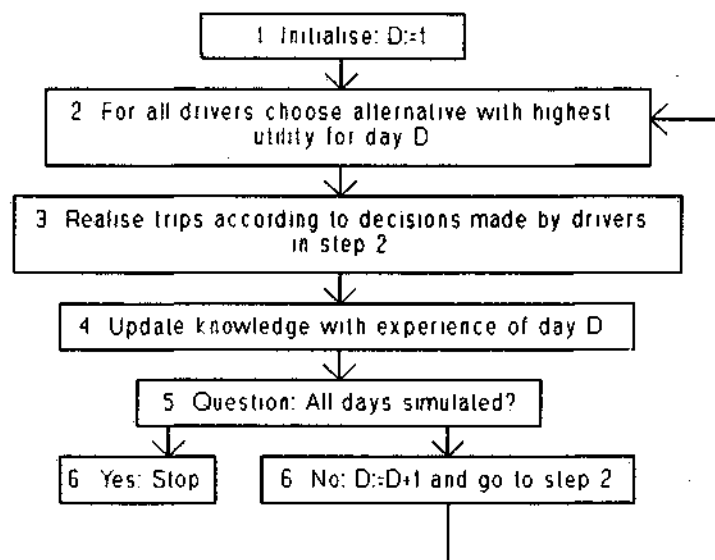


Figure 3: Schematic presentation of pre-trip version of model

⁷The contrary of a individual user optimum is a system optimum in which the performance of the system as a whole is optimised instead of the individual drivers' performances. It is well known from the literature that these two optima often differ. Inequality between individual user optimum and system optimum is for example the reason for the existence of the Braess's paradox (Braess, 1968). See for details also Sheffi (1985). It appears to be an intriguing but extremely difficult question to identify under which conditions an individual user optimum equals a system optimum in a real-world transport network.

The network of major roads in a transport system can be subdivided into a number of edges. Each edge represents a part of the road system.

In the initial situation the speed of a driver on an edge is supposed to be only dependent on the density on that edge.⁸ The mathematical specification for the speed-density relationship used for our simulation experiments is derived from Van Beek et al. (1991) and can be found in the Appendix.

By using this method of generating traffic flows, it is noteworthy that situations can arise in which unrealistically large numbers of drivers want to enter a specific edge. The reason is that in such a model specification all these drivers will enter this edge because there is no way of preventing it. Therefore, in our model we impose for all edges maximum densities and maximum flows.⁹ This is illustrated in Figures 4 and 5, respectively.



Figure 4: A case of maximum flows

Assume that in Figure 4 the maximum flow of both e_1 and e_2 during a certain period is 10, while during this period 12 drivers of edge e_1 want to enter edge e_2 . Then actually only 10 drivers can enter e_2 , so that two drivers have to wait until a new network update.

Next, we may also investigate a network consisting of the following edges (see Figure 5):

We assume that the maximum flow of the edges e_1, \dots, e_5 equals 10, while the maximum density of these edges equals 20. The current situation in this network is displayed in Table 1.

⁸ Some other studies assume that travel time is the sum of free-flow travel time plus the time lost at bottlenecks. For example, Arnott et al. (1991) assume that travel time at a bottleneck equals $D(t)/s_j$, in which $D(t)$ denotes the number of vehicles in the queue on route j and s_j the flow capacity of the bottleneck on route j . Nevertheless, the assumptions underlying these studies appears to be the same as in our model.

⁹ Non-recurring congestion can be taken into consideration by making the maximum flows stochastic.

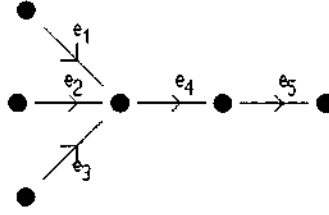


Figure 5: A case of maximum density

Table 1: Current situation in network of Figure 5

edge	current density	number of drivers willing to enter next edge
e_1	14	4
e_2	12	3
e_3	15	5
e_4	15	4
e_5	12	0

When all drivers who want to enter the next edges actually enter these edges, the maximum density of edge e_4 will be exceeded. The current density of e_4 is 15 and 4 drivers want to leave e_4 , so that $20^{10} - (15 - 4) = 9$ drivers of edges e_1 , e_2 and e_3 can enter edge e_4 , while 12 drivers want to enter e_4 . Thus 3 drivers have to wait till the next network update. An algorithm has been built to generalise the above mentioned checking process for any arbitrary network. The exact algorithm, propositions and features can be found in Emmerink (1992).

As indicated in the previous section, the drivers' behaviour is modeled by using random utility theory. This means that each driver decides on which alternative to choose according to an individual utility function. We will use here a linear utility function which defines the utility of driver i for route j and departure time t for day T in the following way:

¹⁰ The maximum density of edge e_4 is 20.

$$U_j^i(t,T) = \beta_1^i * D(j) + \beta_2^i * ET(i,j,t,T) + \beta_3^i * H(i,j,t,T) + \beta_4^i * TP(i,t) + \epsilon_j^i(t) \quad (4.1)$$

with

$$\begin{aligned} D(j) &= \text{distance of route } j \\ ET(i,j,t,T) &= \text{expected travel time of driver } i \text{ on day } T \\ &\quad \text{by choosing route } j \text{ and departure time } t \\ H(i,j,t,T) &= \text{habitual component of driver } i \text{ for route } \\ &\quad j \text{ and departure time } j \text{ at day } T \\ TP(i,t) &= \text{time preference component of driver } i \text{ for} \\ &\quad \text{departure time } t \\ \epsilon_j^i(t) &= \text{normal distributed disturbance term } N(0, \sigma_{ij,t}^2) \end{aligned}$$

The parameters β_1^i and β_2^i are of course negative, while β_3^i and β_4^i have a positive sign. Utility function (4.1) implies a Probit-model for each driver.

We specify the habitual component as follows:

$$\begin{aligned} H(i,j,t,T) &= c_i(T) * 1 + (1 - c_i(T)) * H(i,j,t,T-1), \text{ if on day} \\ &\quad T-1 \text{ route } j \text{ and departure time } t \text{ are chosen.} \\ &= z_i(T) * H(i,j,t,T-1), \text{ otherwise} \end{aligned}$$

$c_i(T)$ falls in the interval $[0,1]$ and $z_i(T)$ in $[0,1]$, so that $H(i,j,t,T)$ falls also in $[0,1]$. This specification implies that the habitual component of a given alternative increases if it is actually chosen, and decreases otherwise.

The time preference component can be specified for example by means of the curve in Figure 6. This figure shows that this driver prefers to depart at time t_0 .

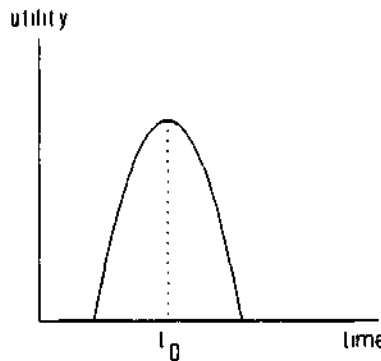


Figure 6: Example of the time preference component

Different ET-specifications are described in Section 5.

5 Information Mechanisms

The expected travel time component in the utility function will be used to model different information mechanisms. Here we assume that the information a driver receives is only used in the travel time forecasting process, i.e., only in the ET specification.

Four different travel time forecasting processes will be described. The first one is very simple, while the last one describes a dynamic on-route forecasting process.

1st travel time forecasting process

For the first travel time forecasting process the following ET-specification is used:

$$\begin{aligned} ET(i,j,t,T) &= a_i(T) * TT(T-1) + (1-a_i(T)) * ET(i,j,t,T-1), \text{ if} \\ &\text{on day } T-1 \text{ route } j \text{ and departure time } t \text{ are chosen by driver } i. \\ &= ET(i,j,t,T-1), \text{ otherwise.} \end{aligned}$$

$TT(T-1)$ denotes the actual travel time of driver i at day $T-1$ and $a_i(T)$ falls in the interval $[0,1]$. This specification implies that a driver receives information about the network only by own travel experience. Horowitz (1984) used this specification in his most complex and realistic model, and analysed it by means of simulations.

2nd travel time forecasting process

In the second travel time forecasting process drivers do not only use their own travel experience for forecasting future travel times, but receive also information about the fictive travel times of the alternatives not chosen. To model this process we need the following modifications. We first define:

$$RTTN(i,j,t,T-1) = \text{real travel time at day } T-1, \text{ if route } j \text{ and departure time } t \text{ was chosen by driver } i$$

Then the new ET specification is

$$\begin{aligned} ET(i,j,t,T) &= a_i(T) * RTTN(i,j,t,T-1) + \\ &(1-a_i(T)) * ET(i,j,t,T-1) \end{aligned} \quad (5.1)$$

This ET-specification differs only slightly from the specification in the first forecasting process, but makes a big difference for the drivers in the network. The latter specification provides them every day with information on all alternatives, while the

former one only updates the expected travel time of the alternative chosen.

In this specification the interaction between drivers' behaviour and the information provision can already be seen, since route and departure time decisions are based among other things on the information from the last travel period, while the information in the next period is dependent on the actual decisions made by the drivers before.

3rd travel time forecasting process

The third travel time forecasting process is equal to the second travel time forecasting process combined with a pre-trip mechanism. In this mechanism drivers will be informed before the start of a trip about the actual situation in the network. To model this mechanism we first use the second travel time forecasting process, i.e., equation (5.1), and rename ET from equation (5.1) into ET2. Then we specify the variable PTTT(j, t_0, T) as the expected pre-trip travel time for route j with departure time t_0 on day T on the basis of the current situation in the network at an arbitrary time t_0 . Furthermore, we specify the expected travel time for route j with departure time t_1 on day T calculated at moment t_0 (this only makes sense if $t_1 > t_0$) as follows:

$$\begin{aligned} ET(i, j, t_0, t_1, T) = & g(t_0, t_1) * PTTT(j, t_0, T) + \\ & (1 - g(t_0, t_1)) * ET2(i, j, t_1, T) \end{aligned} \quad (5.2)$$

$g(t_0, t_1)$ is a function with values in the interval $[0, 1]$, and increases in t_0 by a fixed t_1 .

For the explanation of this mechanism we assume that an arbitrary driver i has n different possible departure times $t_1 < t_2 < \dots < t_n$. We also assume that the actual time on day T is t_c and $t_c \in \{t_1, \dots, t_n\}$. The optimising process of driver i can then be described as follows:

For all $t \in \{t_1, \dots, t_n\}$ compute $ET(i, j, t_c, t, T)$ (see equation (5.2)).

Choose route k and departure time d according to the highest utility, with $ET(i, j, t_c, t, T)$ substituted into the utility function. Driver i starts his trip, if d equals t_c . Otherwise, driver i stays for the time being at home and the process is repeated at the moment when the next t_c -value equals the next departure time of driver i .

Schematically the optimising process is shown in Figure 7.

So in this mechanism drivers are forecasting travel times using among other things

the current situation in the network.

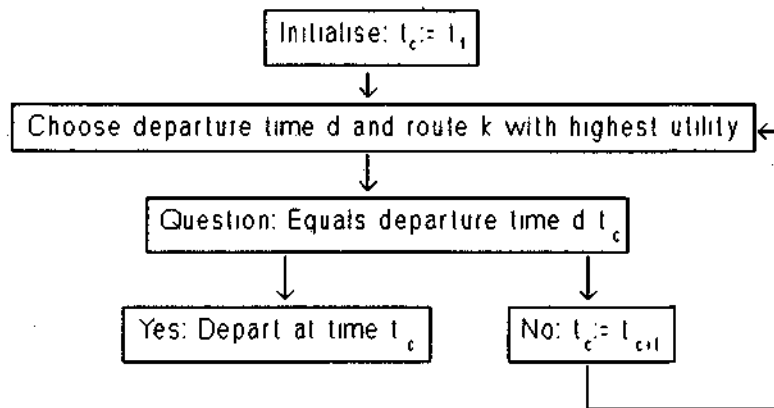


Figure 7: Optimising process for an arbitrary driver

4th travel time forecasting process

The last modeled travel time information mechanism is an RTI (real-time information) system. The mechanism consists of two parts. The former one is the pre-trip decision process and can be modeled by using one of the three above mentioned mechanisms. A new formulation is required for the latter part. Therefore we assume that drivers, equipped with an RTI-system, change routes during the trip on the basis of a utility function like (4.1), in which the departure time is omitted.

During every network update the actual values of the utility function are calculated or estimated. So drivers, equipped with an RTI-system, have the opportunity to change routes at every network update moment. Now it is clear that in Figure 3 of Section 4, steps 2 and 3 have to be modified. This implies that the route decision before the start of the trip can be changed during the trip as a result of the information given by the RTI-system.

6 Simulation Experiments for Amsterdam

In this section we will present results of some simulation experiments for the road system in Amsterdam. The simulations are carried out for the first travel time forecasting process, in order to identify some of the basic difficulties and features of our approach. The simulation program is written in the language C. The congested network, used for the simulations, concerns the major roads around Amsterdam in 1989 and is

displayed in Emmerink (1992). We assume here for the ease of presentation that drivers make only route choice decisions, so that departure times are fixed. This implies that the time preference (TP) component in the utility function vanishes. The drivers are subdivided into 15 different types of each 150 drivers. Drivers of the same type are identical in all respects, except departure time. It is assumed that the departure times of drivers within a type are according to one of the following two lines.

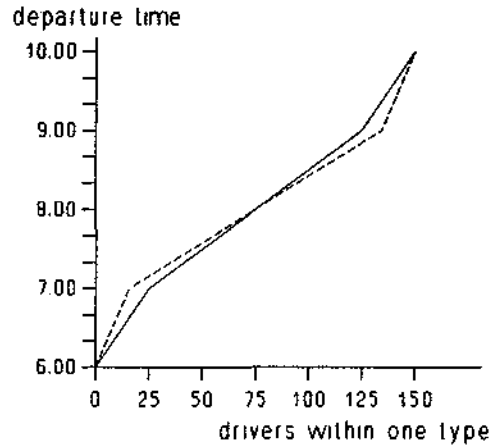


Figure 8: Departure times within a given type

Figure 8 indicates that the first driver of a given type departs at 6.00 am and the last driver of this type departs at 10.00 am. The uninterrupted line implies that two out of three drivers depart between 7 and 9 am. On the other hand, the dashed line implies that four out of five drivers depart between 7 and 9 am. So the departure times are more equally distributed in the uninterrupted case. Furthermore, it is assumed that drivers choose between at most three pre-determined different routes. This assumption is not as restrictive as it seems because most drivers will only have three reasonable different route choice options in the network of major roads around Amsterdam. Furthermore, we assume that the parameters are equal for all drivers. Thus the utility function has the following form:

$$U_j(T) = \beta_1 * D(j) + \beta_2 * ET(i,j,T) + \beta_3 * H(i,j,T) + \epsilon_j \quad (6.1)$$

The performance measures used for our transport system are the overall Average Travel Time (AT) and the overall Average Travel Distance (AD).

In the simulations the parameter $a_i(T)$ is fixed at 0.4, the parameter $c_i(T)$ at 0.3 and

the parameter $z_i(T)$ at 0.7.

The first simulations are performed with the use of a deterministic utility function.¹¹

Table 2 displays the results.

Table 2: Deterministic simulation results

β_1	β_2	β_3	AT(100)	AD(100)	AT(100)	AD(100)
0	-3	0	12.62	24.40	16.33	24.67
-1	0	0	12.84	23.60	16.94	23.60
-1	-3	1	11.97	23.77	15.54	24.10
-1	-3	3	12.20	24.08	15.46	24.02
-1	-3	5	12.01	24.05	15.45	24.01
-1	-3	10	12.08	23.82	15.42	23.90

The first column shows the parameter combinations used; the second column represents a system in which two out of three drivers depart between 7 and 9 am, while in the last column four out of five drivers depart between 7 and 9 am (see Figure 8). Furthermore, AT(100) and AD(100) are the performance measures at the 100th simulated day. AT is measured in 2 minutes (12.62 implies 25.24 minutes) and AD in kilometers. Figure 9 gives the AT performance measure during the simulated days for the system with parameters $\beta_1 = -1$, $\beta_2 = -3$ and $\beta_3 = 1$.¹²

¹¹ This implies that the disturbance term in (6.1) is omitted.

¹² The other tabulated systems show similar patterns.

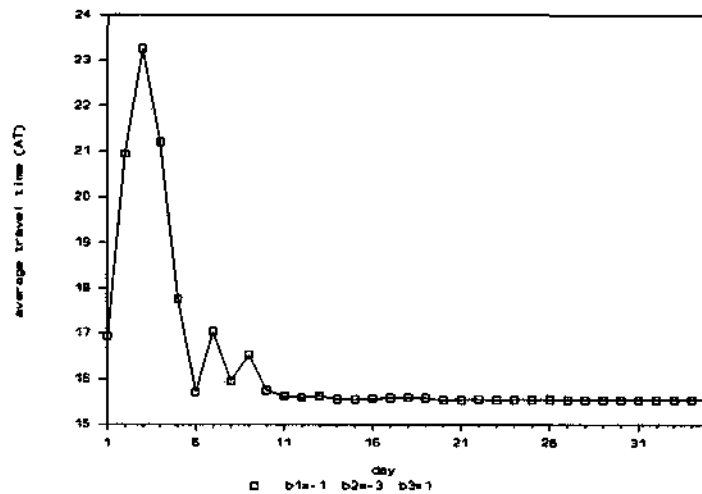


Figure 9: AT performance measure during the simulated days

The results of these simulations can be interpreted as follows:

- 1) The system converges for all the β parameters chosen. After 15 simulated periods the fluctuations are already very small. So despite the fact that - due to the interactions between the drivers - a transport network is very complex, the system converges quite fast.
- 2) The average speed in the network is in the first column 60 km/h and in the second column 50 km/h; this means a high degree of congestion for a network of highways.
- 3) The difference in average travel time between the two different systems is about 8 minutes. This is strikingly large, so that departure time 'distribution' is likely to be an effective tool for diminishing the congestion problem.
- 4) The more weight is given to the habitual component, the sooner the system converges.
- 5) By comparing the one system with parameter values $\beta_1=0$, $\beta_2=-3$, $\beta_3=0$ to the system with parameter values $\beta_1=-1$, $\beta_2=-3$, $\beta_3=5$, it appears that in the former one the AT-value is higher. The interpretation of this result is that the aim of only minimising travel time will not always yield the actual lowest travel time. It sometimes appears to be useful to maximise a more extended utility function. Throughout the paper this paradox will be called the travel time minimising paradox. In the next simulations we will return to this paradox and try to find out whether this also appears in stochastic

systems.

The next simulations are performed with a stochastic utility function. Thus the disturbance term in formula (6.1) is not omitted. In stochastic systems, it is generally necessary to perform many simulations in order to get significant results. The following experiment is set up to examine whether the above mentioned paradox also appears in stochastic systems. Therefore, 100 simulations are carried out for a system in which only travel time is minimised, and another 100 simulations for a system in which a more extensive utility function is maximised. The parameters of this utility function are $\beta_1 = -1$, $\beta_2 = -3$, $\beta_3 = 5$, while the variance of the normal distributed disturbance term is 12.5. The parameters of the travel time minimising system are $\beta_1 = 0$, $\beta_2 = -3$, $\beta_3 = 0$ and the variance is 5. Different variances are chosen to make the systems comparable.¹³ Figure 10 and Table 3 give the simulation results.

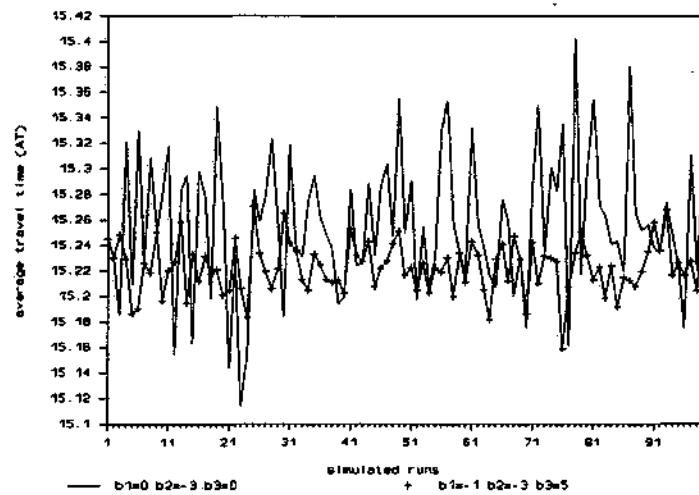


Figure 10: Testing the travel time minimising paradox

¹³ Different variances are necessary because utility levels are not equal in both systems. Similar variances would lead to a larger influence of the disturbance term in the system with the lowest utility level.

Table 3: Mean and variance of simulated runs

	$\beta_1=0, \beta_2=-3, \beta_3=0$	$\beta_1=-1, \beta_2=-3, \beta_3=5$
mean	15.257	15.223
variance	0.002897	0.000407

Testing the differences of the 100 simulations gives a value of -5.94 for the normal distributed test variable.¹⁴ This implies that the means of the two simulated runs differ significantly. Thus only minimising travel time leads to a higher average travel time compared with the more general system. Another striking result is the fact that the variance of the travel time minimising run is about six times as high as the variance in the other run.

The travel time minimising paradox will now be tested once more. We use the same experiment, but the $a_i(T)$ parameter is changed from 0.4 to 0.8. This implies that the prediction of the future travel time is strongly based on the last travel experience of an alternative. The results are given in table 4.

Table 4: Testing the travel time minimising paradox with parameter $a_i(T)=0.8$

	$\beta_1=0, \beta_2=-3, \beta_3=0$	$\beta_1=-1, \beta_2=-3, \beta_3=5$
mean	16.265	16.238
variance	0.278	0.0676

The results in Table 4 lead to the following interpretation:

- 1) The mean travel times are, compared to the system in which $a_i(T)$ is 0.4, higher. This implies that the system as a whole functions worse if expected travel times strongly rely on the last trip experience.
- 2) Variances are compared with Table 3 extremely large. Intuitively this can be explained

¹⁴We have tested the differences of the two simulated runs. If X_i denotes the i^{th} observation in the first simulation run and Y_i the i^{th} observation in the second run ($i=1, \dots, 100$) then the differences $X_i - Y_i$ are tested. If we assume that X_i and Y_i are normally distributed, then testing the differences corresponds to the well-known Behrens-Fisher problem. See, for example, Lehmann (1959).

by the fact that the fluctuations in the ET component are stronger.

3) Also in this experiment the variance in the travel time minimising system is much higher than in the more general system (see also Table 3).

4) Testing the differences leads to a value of -0.32 for the standard normal distributed test variable. Thus the paradox is in this case not significant.

7 Conclusions

Despite the simplicity of our travel information model, it contains the main characteristics of a transport network: many variations in behaviour between drivers can be modeled, while also the mutual interactions between the drivers in the network and the interaction between the drivers and the information is incorporated. Moreover, it is possible to model different information mechanisms so that different effects of information can be analysed.

Although the simulations are performed for the simplest information mechanism, they generate already some quite interesting results. In the first place, it turns out that only minimising travel time will not always yield the lowest overall travel time for the system as a whole. A more general utility function may sometimes lead to a lower overall travel time. Secondly the overall travel time increases if the expected travel time strongly relies on the last trip experience. And finally, the variance of the overall travel time is larger in a travel time minimising system compared to a system in which a more general utility function is maximised.

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Appendix

We have used the speed-flow curve proposed by Van Beek et al. (1991). These authors found empirically that the following simple quadratic relation fitted best for a two-lane highway:

$$S = -0.00035 \cdot I^2 + 0.037 \cdot I + 101.0 \quad (A1)$$

in which S represents the speed in kilometers per hour and I the flow per six minutes.

Changing (A1) to flows per hour gives:

$$S = -0.0000035 \cdot I^2 + 0.0037 \cdot I + 101.0 \quad (A2)$$

Substitution of the identity $I = S \cdot D$ in (A2) leads to the following speed-density relationship:

$$S = -0.0000035 \cdot (S \cdot D)^2 + 0.0037 \cdot (S \cdot D) + 101.0 \quad (A3)$$

Finally, solving equation (A3) for S gives:

$$S = \frac{-1 + 0.0037 \cdot D + \sqrt{\{(1 - 0.0037 \cdot D)^2 + 0.0014 \cdot D^2\}}}{0.0000070 \cdot D} \quad (A4)$$

Equation (A4) is used in the computer program.

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